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Towards a generic multi-criteria evaluation model for low carbon cities

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ABSTRACT

The low carbon city concept has surfaced over the past decade and has been increasingly integrated with urban planning. Likewise, assessment methods of Low Carbon Cities have been initiated. Of these, are the Entropy weight method, fuzzy comprehensive evaluation and multi-criteria evaluation. This paper attempts to propose a multi-criteria evaluation model for city performance using a set of criteria and a benchmark with a view to determining whether the city is low carbon or not. Ten pilot cities were selected for which twenty indicators were utilized for model calibration and testing. First, a standard entropy model was employed featuring three cities as low carbon namely; Stockholm, Vienna and Sydney. Second, with the modification of entropy model by adding relative weight to indicators, two more cities were quite rightly added to the list: London and São Paulo. Third, the proposed model was calibrated and tested, the result of which was compared with the results of both entropy and modified entropy models. Luckily, the proposed model showed great similarity to the modified entropy model. Moreover, the model was subsequently tested independently on five additional cities comprising Copenhagen, Bogota, New Delhi, Singapore and Seoul to ascertain results. Copenhagen and Bogota were low carbon cities, the others were not. When populated with relevant data, the proposed model can readily determine whether a particular city is low carbon or not thereby obviating the need for benchmarking and score adjustment every time a new city is added to the study list.

1. Introduction

Though Cities are major centres of economic growth, they are nonetheless the largest producers of global carbon emissions. Rapid urbanisation, coupled with global warming, increasingly threaten environmental quality, social well-being and quality of life (Edstrand, 2015). Some cities have initiated programs to promote reductions of carbon emissions and thereby, mitigate the impacts of climate change. London, for example, attempts to reduce 60% of Green House Gas (GHG) emissions by 2025. Similarly, Rotterdam and Iskandar seek to cut 50% of carbon emissions by 2025 and 2030 respectively. Chicago has set out an ambitious target to reduce 25% by 2020 and 80% by 2050 compared with the 1990 level (Tan et al., 2015).

Various models have been built to measure carbon emissions to substantiate studies of climate change and sustainability. In Beijing for example, nexus modeling of energy and carbon flows was considered with urban size and population density (Chen and Chen, 2016). Liu and Wang (2017) suggested a multiproxy distribute on a system that included a series of transport-related demand and supply indicators. In Oslo MARKAL/TIMES modeling was used to analyse the transition to a low-carbon energy system (Lind and Espegren, 2017).

By building on previous research and filling a gap in the literature, this paper attempts to develop an evaluation method that affords a generic multi-criteria model which can be applied in every city to assess its performance with regard to carbon emissions and subsequently establish whether it is low carbon or not. Ten pilot cities were selected to construct the indicator framework and validation. City selection was based on its carbon emission level and the assessment of credible institutions. The selected cities consisted of Stockholm, Vancouver, London, New York, Johannesburg, Beijing, Sydney, São Paulo, Mexico City and Tokyo. Thereafter, the model was subsequently tested independently on five more cities comprising Copenhagen, Bogota, New Delhi, Singapore and Seoul with a view to ascertain results.

Two assessment methods are used here. First, is the entropy weight method which was originally devised by Tan et al. (2015). The model's criteria and indicators of low carbon city elements includes inter alia, energy, water, land use, air quality, and mobility and builds on the studies of Lin, Jacoby, Cuia, Liu, and Lin (2014); Han, Tang, Fan, Liu, and Wei (2016); and Zhou, He, Williams, and Fridley (2015). It must be noted however, that in Tan et al., (2015), the model has applied equal weight to each criterion, despite differences of carbon emissions levels. However, this deficiency has been rectified by Kourtit, Macharis, and Nijkamp (2014) who have employed multi-actor multi-criteria analysis (MAMCA) to identify the relative importance of indicators and cities.

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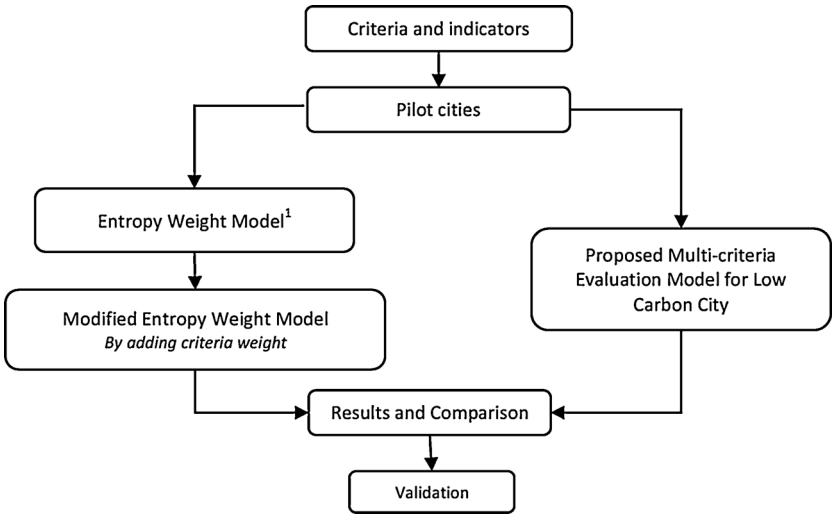

Fig. 1. Research Framework.

Apparently, human activities produce most carbon emissions, the preponderance of which comes from combustion of fossil fuels (Poumanyvong and Kaneko, 2010). In fact, the International Energy Agency has identified three sectors that use fossil fuels and appreciably contribute to carbon emission levels, namely; electricity/heat, transportation, and industry. This study draws on seven sources as references to determine the weight of each category which proved helpful in refining the proposed evaluation model. Arguably, the addition of weight to the proposed model has made it more realistic as it accommodates real condition of city and changes its score and results which were derived by previous research.

Second, is a proposed evaluation model that has been formulated to afford a summary of multi-dimensional criteria thereby facilitating the determination of a city being low carbon or not. Moreover, the proposed model assesses city's performance and readily establish new calculations independently.

2. Literature review

Over the past few decades, economists and operations researchers have been concerned with building optimisation decision-making tools which are widely known as multi-criteria analysis (Yager, 2016). Central to this evaluation tool is the qualitative multi-dimensional environmental effects which provide an adequate representation of all relevant criteria (Nijkamp and Voogd, 1980). The criteria could be physical, planning, socio-economic or environmental (Munda, 2003).

Multi-dimensional evaluation models serve two purposes: multivariate data analysis and multi-dimensional decision analysis (Nijkamp and Voogd, 1980). In fact, multi-criteria analysis has been reformed and applied by (Akgun, Leeuwen and Nijkamp, 2012) in their endeavour to evaluate sustainable development. However, Vaz et al. (2012) have noted that their model has been limited to the evaluation and prediction of urban growth pattern and land use development. Likewise, Deveci, Demirel, John, and Ozcan (2015) have confined their analysis to the modeling of strategic development and locational decisions for CO2 storage.

It is widely held that the well-known multi-criteria evaluation is a fuzzy analysis because it deals with uncertainty which in turn increases the complexity of model building (Yatsalo, Korobov and Martínez, 2017). Furthermore, multi-criteria evaluation has taken many forms such as Fuzzy Numbers (FNs), FRAA (Fuzzy Rank Acceptability Analysis) and FMAA (Fuzzy Multi-criteria Acceptability Analysis). It is quite common to combine fuzzy MCDA with weighting indicator to reflect the relative importance of indicators in determining the overall performance. Known as entropy weight, this method employs parameters which describe certain attributes using specific scoring methods (Becker, Saisana, Paruolo, & Vandecasteele, 2017). Originally, entropy belongs to the area of thermodynamics on nonlinear theory. The value of entropy reflects the state of order of a system (Wang et al., 2015). Recently, the Entropy Weight Coefficient Method (EWCM) has been recognisably used to evaluate sustainable development (see (Qi, Wen, Wang, Li, & Singh, 2010) and (Han et al., 2016)).

In an effort to measure sustainability performance, various models have been proposed. Munda (2003) has employed multi-criteria to measure the economic impact on ecological cost by indicators. Sala, Ciuffo and Nijkamp (2015) have formulized Sustainability Assessment (SA) in a structured procedure involving analytical methods and models from various fields (Sala et al., 2015). They went on to conduct scenario design using various measurable multi-criteria and indicators. Furthermore, by developing an objective weighting approach of interdependent criteria, Zhang, Xu, Yeh, Liu, and Zhou (2016) built a model that is equipped with novel optimization on multi-level hierarchy and tested this on 13 cities in China.

3. Methodology

The authors have initiated this study by identifying criteria and indicators which are widely used in sustainability and energy efficiency. Then, ten pilot cities were selected to construct the indicator framework comprising Stockholm, Vancouver, London, New York, Johannesburg, Beijing, Sydney, São Paulo, Mexico City and Tokyo. The authors have also refined Tan et al. (2015) model by adding weight to criteria and obtaining new results which were subsequently used to compare with the proposed model (Tan et al., 2015). Tan's model requires several samples of cities to calculate the benchmark and rank and of a city; when done the same has to be repeated with the addition of a new city to the list. On the contrary, the proposed model allows the addition of new cities without re benchmarking and readily establish new calculations independently. In other words, the proposed model is generic and can be employed to assess new cities other than pilot cities (Fig. 1).

3.1. Criteria and indicator selection

Initially, a group of criteria has been identified, namely; economic, energy, land use, carbon emission level, transportation, water and waste. Quantifiable indicators under each criterion are then selected to measure carbon performance and compare it with the low carbon city benchmark (Tan, Yang and Yan, 2015).

Benchmark setting is important because it aims to sufficiently differentiate between cities of various performance. In other words, benchmark should not be too high to the extent that makes low-performance city difficult to be differentiated and *vice versa*. Tan et al.

Table 1
List of criteria and indicators for Low Carbon City.
(Source: Tan et al., 2015).

Criteria	Indicator	Effect	Unit of measurement	Benchmark value	Source
Economic	GDP per capita	+	$/capita	12616	(World Bank, 2013)
	Proportion of tertiary industry to GDP	+	%	66	(World Bank, 1995)
	Carbon Productivity	+	USD/ton	12244	(Siemens, 2015)
Energy	Proportion of renewable energy	+	%	18.76	(Siemens, 2015)
	Energy intensity	−	MJ/USD	1.47	(Siemens, 2015)
Land Use	Proportion of public green space	+	%	50	(Wien International, 2015)
	Population density	−	People/km^2	4236.1	(MERCER, 2015)
Carbon and environment	CO2 emissions per capita	−	Ton/person	2.19	(Zhou et al., 2015)
	Nitrogen dioxide emission/capita	−	μg/m^3	40	(WHO, 2006)
	Daily sulphur dioxide level	−	μg/m^3	20	(WHO, 2006)
	Daily suspended particular matter levels	−	μg/m^3	20	(WHO, 2006)
Transportation	Public buses per capita	+	buses/million persons	994	(Siemens, 2015)
	Rail length per capita	+	km/million persons	51.7	(Siemens, 2015)
	Cars per capita	−	Private cars/persons	0.34	(Siemens, 2015)
Waste	Solid waste generation per capita	−	Kg/capita/day	0.8	(World Bank, 2012)
	Share of waste collected and adequately disposed	+	%	100	(World Bank, 2012)
	Share of waste to energy	+	%	0.5	(ADEME, 2013)
	Share of material recycling	+	%	60	(ADEME, 2013)
Water	Share of wastewater treated	+	%	100	(Zhou et al., 2015)
	Water consumption intensity	−	L/capita/day	52.1	(Zhou et al., 2015)

(2015) have derived the benchmarks from many resources: (1) benchmarks established by international organizations, for examples, World Bank and WHO; (2) benchmarks of cities with top performances, for examples, Green City Index proposed by Siemens that includes Venice and Copenhagen; (3) benchmarks of International targets for developed countries, for example, renewable energy target set by EU.

Relevant data were then gathered for each indicator from multiple sources. Benchmark values have been used as input to determine the minimum score of low carbon characteristics (Table 1).

3.2. Entropy weight model

Entropy weight method is used for many purposes, including policy monitoring, communication to the public and generation of rankings. It also provides a benchmark, the reference to which city performance can be measured (Wang et al., 2015).

Here, indicators are aggregated in a weighted average to calculate composite indicators which are employed to assess complex variables that are not measurable and or difficult to define (Tan, Yang et al., 2015; Chaji, 2017).

In this study, the authors have assigned weight for each criterion to improve entropy model. This was followed by data normalization because indicators consist of data with the different dimensions and units. Whereas Eq. (1) is proposed to normalize data for indicators with positive effects on carbon emissions level, Eq. (2) is proposed for indicators with negative effects.

$$r_{ij} = \frac{x_{ij} - min_j\{x_{ij}\}}{max_j\{x_{ij}\} - min_j\{x_{ij}\}} \tag{1}$$

$$r_{ij} = \frac{max_j\{x_{ij}\} - x_{ij}}{max_j\{x_{ij}\} - min_j\{x_{ij}\}} \tag{2}$$

where, r_{ij} is the normalized value of the jth object, i^{th} indicator; xij is the original value of the j^{th} object, i^{th} indicator. The $max_j\{x_{ij}\}$ represents the maximum value in the set data of x_{ij} while $min_j\{x_{ij}\}$ represents the minimum value in the datasheet.

Entropy weight coefficient method is used to determine the weight factor of each indicator. The entropy of the i^{th} indicator is defined by Eq. (3):

$$E_i = -k\sum_{j=1}^{n} y_{ij} lny_{ij} \tag{3}$$

where, E_i is the entropy number of the i^{th} indicator; n is the number of evaluated object in the study, i.e., the number of selected cities. y_{ij} is the standardized value of r_{ij}.

The coefficient y_{ij} and k are calculated in Eqs. (4) and (5).

$$y_{ij} = r_{ij}/\sum_{j=1}^{n} r_{ij} \tag{4}$$

$$k = 1/\ln n \tag{5}$$

when $y_{ij} = 0$, we suppose that $y_{ij}lny_{ij}$ is equal to 0.

The weight of each indicator w_i, to a specific category is then calculated in Eq. (6).

$$w_i = (1 - E_i)/\left(m - \sum_{i=1}^{m} E_i\right) \tag{6}$$

where, m refers to the total number of indicators. The score for each indicator is calculated based on the proposed criteria weight.

3.2.1. Score

Aggregate score of indicators is determined by the multiplication of the entropy weight (w_i) with the normalized value (r_{ij}) as shown in Eq. (7).

$$S_l = \sum_{i=1} (w_i \times r_{ij} \times 100) \tag{7}$$

where, $S_l$is low carbon score of the i^{th} criteria. The scores of each criterion are then re-based onto scale of 0–100.

3.2.2. Criteria weight

Many researchers have attempted to evaluate low carbon cities performance, of these were (Tan et al., 2015), (Wang et al., 2015) and (Zhou et al., 2015). They have assigned equal weight for each category, despite the fact that some categories have higher contribution than the others. A certain weight in each sector is derived from several sources from credible international reports and organizations.

This paper seeks to refine the evaluation method by adding relative weight to each to each criterion and operationalise the evaluation

Table 2
Basic model of proposed multi-criteria evaluation for low carbon city scoring model.

Indicator	Unit of measurement	formula	y_{ic}	S_c	Subtotal ($S_c \times w_c$)
GDP per capita	$/capita	$y_i = \frac{\ldots - 12616}{12616}$	…	…	**Economy** … X 18% = …
Proportion of tertiary industry to GDP	%	$y_i = \frac{\ldots - 66}{66}$	…		
Carbon Productivity	USD/ton	$y_i = \frac{\ldots - 12244}{12244}$	…		
Proportion of renewable energy	%	$y_i = \frac{\ldots - 18.76}{18.76}$	…	…	**Energy** … X 20.5% = …
Energy intensity	MJ/USD	$y_i = \frac{1.47 - \ldots}{1.47}$	…		
Proportion of public green space	%	$y_i = \frac{\ldots - 50}{50}$	…	…	**Land Use** … X 9% = …
Population density	people/km^2	$y_i = \frac{4236.1 - \ldots}{4236.1}$	…		
CO2 emissions per capita	ton/person	$y_i = \frac{2.19 - \ldots}{2.19}$	…	…	**Carbon and Environment** … X 20.5% = …
Nitrogen dioxide emission/capita	μg/m^3	$y_i = \frac{40 - \ldots}{40}$	…		
Daily sulphur dioxide level	μg/m^3	$y_i = \frac{20 - \ldots}{20}$	…		
Daily suspended particular matter levels	μg/m^3	$y_i = \frac{20 - \ldots}{20}$	…		
Public buses per capita	buses/million persons	$y_i = \frac{\ldots - 994}{994}$	…	…	**Transportation** … X 19% = …
Rail length per capita	Km/million persons	$y_i = \frac{\ldots - 51.7}{51.7}$	…		
Cars per capita	Private cars/persons	$y_i = \frac{0.34 - \ldots}{0.34}$	…		
Solid waste generation per capita	kg/capita/day	$y_i = \frac{0.8 - \ldots}{0.8}$	…	…	**Waste** … X 6.5% = …
Share of waste collected and adequately disposed	%	$y_i = \frac{\ldots - 100}{100}$	…		
Share of waste to energy	%	$y_i = \frac{\ldots - 0.5}{0.5}$	…		
Share of material recycling	%	$y_i = \frac{\ldots - 60}{60}$	…		
Share of wastewater treated	%	$y_i = \frac{\ldots - 100}{100}$	…	…	**Water** … X 6.5% = …
Water consumption intensity	L/capita/day	$y_i = \frac{52.1 - \ldots}{52.1}$	…		
TOTAL (S_t)					…

model. The final score calculation formula can be seen in Eq. (8).

The relative weight of criteria is shown in Eq. (8).

$$S_c = \sum_{i=1} (w_c \times S_i \times 10) \tag{8}$$

where S_c is the total score of all categories, w_c is weight factor of c^{th} category, S_i is low carbon score of the i^{th} criteria.

3.3. Proposed multi-criteria evaluation model

Basic model of proposed multi-criteria evaluation model can be seen in Table 2. Dataset of each city can be seen in Appendix A, Table A1.

3.3.1. Data normalization

The equation of data normalization is set out in Eqs. (9) and (10).

$$y_i = \frac{x_i - x_b}{x_b} \tag{9}$$

$$y_i = \frac{x_b - x_i}{x_b} \tag{10}$$

where y_i is normalized data of assessed object on i indicator, x_i is original value of the object on i^{th} indicator, x_b is benchmark value of i^{th} indicator. While Eq. (9) is used for indicators with positive effects on carbon emissions level, Eq. (10) is used for indicators with negative effects.

3.3.2. Weighting factors

The calculation of proposed evaluation model is shown in Eq. (11).

$$S_t = \sum_{c=1} (S_c \times w_c) \tag{11}$$

where S_t is the total score of assessed city, w_c is the weight factor of c category, and S_c is total score of y_{ic} in c^{th} category.

4. Results

The result of the proposed multi-criteria evaluation model for low carbon city will be compared with the modified entropy weight model but will be preceded by the following calculations.

4.1. Relative weight of criteria

Relative importance of each criterion has been assigned a weight to reflect contribution of carbon emission level (Table 3).

Relative weights of factors have been compiled from different sources such as the reports of international organizations and published research. Apparently, energy and carbon and environment are the dominant sectors contributing approximately 41% of carbon emission in a city. The main users falling under this sector are industrial, residential, and commercial uses (Lind and Espegren, 2017). Transportation accounts for 19% of carbon emissions by reason of movement of goods and people by automobiles. Likewise, industrial sector is another high carbon emission source because it directly uses fossil fuel to create heat and steam needed at various stages of production

Table 3
Relative criteria weights.

Criteria	Weighting factor
Economic	18%
Energy	20.5%
Land Use	9%
Carbon & environment	20.5%
Transportation	19%
Waste	6.5%
Water	6.5%

Adapted from International Energy Agency, 2012; EPA, 2015; WDI, 2015; IPCC, 2006; and Global Atmospheric Research, 2000.

Table 4
Criteria weight by model tied.

Entropy Weight Model[1]		Modified Entropy Weight Model	
Cities	Score	Cities	Score
Stockholm	65.87	Vancouver	87.793
Vancouver	57.36	Stockholm	87.413
Sydney	56.19	São Paulo	84.282
Benchmark	**55.56**	Sydney	72.687
São Paulo	54.26	London	65.946
London	49.73	**Benchmark**	**65.802**
Mexico City	42.82	Johannesburg	59.207
Tokyo	39.68	Mexico City	57.554
Johannesburg	39.49	New York	53.479
New York	38.71	Tokyo	52.180
Beijing	34.53	Beijing	32.811

[1]Tan et al. (2015).

Table 5
Result of proposed multi-criteria evaluation model.

Pilot Cities	Score
Vancouver	1.750
São Paulo	1.534
Stockholm	1.492
Sydney	0.557
London	0.151
Benchmark	**0**
Tokyo	−0.311
New York	−0.700
Mexico City	−1.116
Johannesburg	−1.287
Beijing	−4.346

(Shi, 2003). In some industries such as cement plants large amount of fossil fuel are burnt thereby emitting substantial amounts of carbon.

4.2. Comparison between entropy and proposed multi-criteria evaluation model

Table 4 shows that there are differences in score and city rank due to multiplication of relative weight with entropy weight model which was propounded by Tan et al. (2015). On top of the entropy model was Stockholm with a score of 65.87 which has become second to Vancouver under the modified entropy model with a score of 87.79. Additionally, the benchmark under entropy model stood at 55.56, a score that has risen to 65.80. Due to the calculations of entropy weight under the modified entropy weight model, London and São Paulo have exceeded the benchmark and were consequently classed as low carbon cities.

4.3. Validation of the proposed multi-criteria evaluation for low carbon city scoring model

Table 5 shows the result of the proposed multi-criteria evaluation model. The benchmark is set at 0. Any score that is ≥ 0 classes the city as low carbon. The converse holds good, any score that is < 0 means the city is not low carbon. Five cities have been classed low carbon, namely; Vancouver, Stockholm, São Paulo, Sydney, and London. Wang and Chi (2016) have noted that the economic activities of Vancouver, Stockholm and São Paulo not centred on a heavy industry that usually produces high carbon emissions which justifies high scores. Furthermore, they have advanced programs in promoting renewable energy. Similarly, London has an overall score that exceeds the benchmark and hence classes the city as low carbon.

By contrast, Johannesburg, Mexico City, New York, Tokyo, and Beijing have not been categorised as low carbon cities. Heavy industrial activities and high population density appear to have contributed to high carbon emissions because of high demand for electricity and gasoline (Omann, Stocker and Jager, 2009; Lehmann, 2012). Understandably, Beijing has not measured well under the transportation sector criteria due to reported air pollution and traffic jams (KeTTHA, 2011).

Table 6
Result of Tested Cities.

Cities	Score
Bogota	0.8929
Copenhagen	0.0894
Singapore	−0.3116
Seoul	−0.6386
New Delhi	−3.3026

Generally speaking, the result of the proposed multi-criteria evaluation model is markedly similar with the modified entropy model despite slight differences in the rank of cities. Further analysis can be conducted by examining the score in each criterion for evaluation and decision making in the future (Appendix A, Table A2). Result suggests that the proposed model could be reliably used to determine low carbon city.

Furthermore, we tested the model independently on a sample of cities that were chosen to verify model's efficacy and applicability to any city. The result of the test can be seen in Table 6. As can be seen from this table, Bogota and Copenhagen are categorised as low carbon cities, Singapore and Seoul are nearly non-low carbon cities because they fell short of energy and carbon and environment performances (Appendix A Table A4). New Delhi on the other hand, has not measured up well and hence needs serious efforts to be a low carbon city.

5. Conclusion

Low carbon city concept is being adopted by many cities as an appropriate solution to try and tackle carbon emissions. Entropy weight assessment methods have been widely used to evaluate city performance and conclude whether cities are low carbon or not. This paper has attempted to propose a generic multi-criteria evaluation model to independently measure city performance identify whether the city is low carbon or not.

The researchers hope that local governments, investors and the community wishing to measure low carbon city performance quantitatively at micro level, might find the proposed model conducive to their purposes. Investors for example might entertain performance evaluation of city's economy prior to making investment decisions.

In the beginning, the paper refined Tan et al. (2015) evaluation model which uses entropy weight and a set of widely used criteria dealing with economy, transport, energy etc in ten selected cities. The authors have modified Tan et al. (2015) model by adding relative weight to each criterion because of its effect on score calculation. This has allowed for a comparison between results. Energy use and carbon and the environment criteria are the major contributors to carbon emission, followed by transportation and economic. The economic sector, against which London and Sao Paolo have measured well, meant that these two cities quite rightly become low carbon.

Parallel to this, the authors formulated a new multi-criteria model using the same indicators that are used by Tan et al. (2015) so the results could be compared for validation. The result of the proposed model showed great similarity with the modified entropy model and this in turn suggests greater reliability to use it as a generic model for low carbon cities. Cities with abundant data which are typical of developed countries lend themselves to low carbon city evaluation. When indicators are simplified and made more generic, evaluation of developing world cities might become more feasible, thereby enabling more comparative analysis.

Appendix A

See Table A3.

Table A1
Detailed data of pilot cities for proposed multi-criteria evaluation model.

Indicators	Unit	Benchmark	London[1]	Stockholm[2]	New York[3]	Tokyo[4]	São Paulo[5]	Beijing[6]	Vancouver[7]	Mexico City[8]	Sydney[9]	Johannesburg[10]
Per capita	$/capita	12616	51978	53941	63238	41446	39799	20275	16768.79	19940	45377	17418
Proportion of tertiary industry to GDP	%	66	88.9	80.2	91.9	78.4	76	77.3	81	77.2	82.4	80.3
Carbon productivity	$/t	12244	10252	18252.91	1269.33	8868.13	28427.86	2472.56	3808.81	13400	37197.8	11737
Proportion of renewable energy	%	18.76	14	48	23	6	54.5	4.5	90	17	13	12.19
Energy intensity	MJ/$	1.47	2.77	2.2	2.99	1.2	0.55	7.94	1.69	3.39	7.74	0.73
Proportion of public green space		0.35	0.38	0.4	0.14	0.03	0.01	0.56	0.12	0.39	0.46	0.22
Population density	Pop/km^2	4236.1	4887.75	4800	10725.4	6000	7315	1261	5249	5954.2	372.4	2673.87
CO2 emission per capita	t/person	2.19	5.07	2.96	6.35	4.67	1.4	8.2	4.4	1.49	1.22	4.44
NO2 emission per capita	ug/m^3	40	37	15	69.82	39.5	47	52	39.48	60	9	33
sulphur	ug/m^3	20	0.01	2.45	7.34	5.7	4	28	3.14	13	20	16
suspended	ug/m^3	20	22	15	23	33.1	35	121	4.82	93	9	98
Public buses per capita	Public buses/M person	994	903	994	521	162	7142.86	1071	3218	1357.16	474	1394.79
Rail length per capita	Km/M person	51.7	52.5	51.7	44.8	33.6	124.19	38	665.74	403.08	70.5	425.94
Cars per capita	Cars/person	0.39	0.31	0.39	0.21	0.18	0.44	0.25	0.55	0.4	1.5	0.18
Solid waste generation per capita	Kg/capita/d	0.8	0.56	0.28	0.87	1.09	0.55	0.52	0.15	0.49	0.09	1.1
Share of waste collected and adequately disposed	%	100	51	100	44	100	100	95.4	57	100	100	98
Share of waste to energy	%	0.5	0.21	0.49	0.22	0.8	0.35	0.1	0.25	0	0.1	0
Share of material recycling	%	60	34	25	30.4	23.2	1	37	45	56	57	3.3
Share of wastewater treated	%	100	99	100	64	100	81	80.3	55	12.9	99.7	92.5
Water consumption intensity	l/person/d	52.1	157.78	50.88	69.3	320.2	220.5	218.1	137	178	286	348.7

Compiled from: 1. Tan et al. (2015) 'A holistic low carbon city indicator framework for sustainable development', *Applied Energy*. Elsevier Ltd, 185, pp. 1919–1930. doi: 10.1016/j.apenergy.2016.03.041.
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Table A2
Detailed Data of Tested Cities.

Indicators	Unit	Benchmark	Copenhagen[1]	Bogota[2]	New Delhi[3]	Singapore[4]	Seoul[5]
Per capita	$/capita	12616	54386	17500	4300	52960	41126
Proportion of tertiary industry to GDP	%	66	76.4	53	70	95	90
Carbon productivity	$/t	12244	15107	7955	3909	7157	14688
Proportion of renewable energy	%	18.76	18.76	80	12	8	20
Energy intensity	MJ/$	1.47	1.48	0.39	7.7	2.9	3.2
Proportion of public green space		0.35	0.25	0.04	0.22	0.47	0.27
Population density	Pop/km^2	4236.1	6800	4100	11733	7796	17289
CO2 emission per capita	t/person	2.19	3.6	2.2	1.1	7.4	2.8
NO2 emission per capita	ug/m^3	40	12	16	39	5	14
sulphur	ug/m^3	20	2.34	5	7	9	17.2
suspended	ug/m^3	20	24	28	201	49	66
Public buses per capita	Public buses/M person	994	575	1678	690	1000	1429
Rail length per capita	Km/M person	51.7	68	8.1	13.7	36	54.2
Cars per capita	Cars/person	0.39	0.48	0.15	0.04	0.15	0.46
Solid waste generation per capita	Kg/capita/d	0.8	1.83	0.8	0.4	0.8	2.7
Share of waste collected and adequately disposed	%	100	100	99.7	93.6	100	100
Share of waste to energy	%	0.5	0.39	0.35	0.1	2	1.6
Share of material recycling	%	60	23.61	98	17	65	80
Share of wastewater treated	%	100	100	28.6	55	100	100
Water consumption intensity	l/person/d	52.1	402	114.3	208.7	290.7	311

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Table A3
Result of Proposed multi-criteria evaluation for low carbon city model per criteria.

Category	London	Stockholm	New York	Tokyo	São Paulo	Beijing	Vancouver	Mexico City	Sydney	Johannesburg
Economic	0.5948	0.7167	0.6316	0.3955	0.6530	−0.0036	−0.0238	0.1520	0.8790	0.1001
Energy	−0.2333	0.2177	−0.1656	−0.1018	0.5188	−1.0581	0.7478	−0.2870	−0.9373	0.0314
Land Use	−0.0061	0.0009	−0.1919	−0.1198	−0.1528	0.1172	−0.0807	−0.0262	0.1104	−0.0002
Carbon and Environment	−0.0698	0.2872	−0.4432	−0.2173	0.0483	−1.7413	0.1242	−0.7135	0.3624	−0.9332
Transportation	−0.0647	0.2662	−0.4108	−0.2014	0.0448	−1.6139	0.1151	−0.6613	0.3359	−0.8650
Solid Waste	0.0084	0.0000	−0.0096	−0.0422	0.4849	0.0111	0.8908	0.4639	−0.1954	0.5317
Water	−0.0782	0.0030	−0.1106	−0.0244	−0.0631	−0.0572	−0.0239	−0.0441	0.0024	−0.1521

Table A4
Result of tested cities for low carbon city model per criteria.

Category	Copenhagen	Bogota	Delhi	Singapore	Seoul
Economic	0.6664	−0.0288	−0.2303	0.5799	0.5082
Energy	−0.0014	0.8198	−0.9427	−0.3170	−0.2277
Land Use	−0.0802	−0.0768	−0.1927	−0.0448	−0.2979
Carbon and Environment	0.1515	0.1938	−1.6148	−0.4928	−0.3667
Transportation	−0.0640	0.0874	−0.0272	0.0604	0.0582
Solid Waste	−0.1374	0.0215	−0.0702	0.2004	0.0103
Water	−0.4365	−0.1240	−0.2246	−0.2977	−0.3230

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